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A Novel Full-Reference Color Image Quality Assessment Based on Energy Computation in the Wavelet Domain

Abstract: This article presents a novel full-reference (FR) image quality assessment (QA) algorithm by depicting the sub-band characteristics in the wavelet domain. The proposed image quality assessment method is based on energy estimation in the wavelet-transformed image. Image QA is achieved by applying a multilevel wavelet decomposition on both the original and the enhanced image. Next, the wavelet energy (WE) and vector are computed to obtain the percentage of the energy that corresponds to the approximation and the details, respectively. Further, the approximate and detailed energy levels of both the original and the enhanced images are compared to formulate an image quality assessment. Numerous experiments are conducted on a dozen of image enhancement algorithms. The results presented show that the image with poor contrast in the foreground than the background has continuous regular coefficient values. The probability density function for such an image has a relatively lower WE and skewness compared with the background. The proposed scheme not only evaluates the global information of an image but also estimates the fine, detailed changes in an enhanced image. Thus, the proposed metric serves as an objective and effective FR criterion for color image QA. The experimental results presented confirm that the proposed WE metric is an efficient and useful metric for evaluating the quality of the color image enhancement.

Keywords: Image enhancement, quality assessment, wavelet domain, wavelet energy.

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1 Introduction

The heart of any image processing algorithm is the image enhancement [26]. Most of the captured images are of poor quality and need enhancement for further processing. The captured images need further enhancement to correct nonuniform lighting, improve brightness, and contrast. Image enhancement involves the modification of pixel values to make the image easier to interpret and analyze. Image enhancement algorithms [18] are used when we need to pick up some important features in an image, for instance, sharpening the image to bring out details such as a car license plate number, enhancement of edges or lines to pick up buildings or objects in aerial images or some areas of X-ray film for diagnosis. Traditional image enhancement methods such as contrast enhancement [29], histogram equalization [3], and gamma correction [45] are simpler to implement. However, these methods are image dependent. Numerous algorithms [12, 22, 41] have been reported in the literature for both gray-level and color image enhancement. Nowadays, color image enhancement has become a significant research area due to the widespread use of color images in many applications. A color image enhancement algorithm determines the feasibility of applying color in enhancing the image for information extraction. The goal of color image enhancement is to improve the image details, contrast, and sharpness for better visual quality.

In recent years, immense effort has been made to develop an image quality metric for making the best correlation with perceived quality measurement. The image quality assessment (QA) metric [34] plays an important role in the design and evaluation of imaging and image processing systems. The aim of image QA metrics remains same for both compression and enhancement techniques. For instance, in an image compression scheme, the image quality evaluation algorithm [46] may be adapted to evaluate the performance of various image compression algorithms. These image QA algorithms attempt to minimize the number of bits required to store an image while maintaining a sufficiently high image quality. In this article, the image QA metric is developed to evaluate image enhancement techniques similar to compression methods. However, the metrics developed for the image quality evaluation of compression schemes are not applicable for the image enhancement methods.

Over the years, discrete wavelet transform (DWT) has been used for a huge number of image processing applications, replacing the conventional discrete Fourier transform. Although numerous efficient wavelet domain-based objective measures [1, 6, 28] have been reported in the literature, the resulting measure may not perceptually correlate with the human perception, but still, there is a considerable room for improvement in objective image QA. In the present work, DWT has been adapted to evaluate the quality of the enhanced image. Image quality evaluation is important for most image enhancement algorithms. The proposed method exploits the wavelet domain into the human visual system (HVS) [39] characteristics for image QA. This scheme is based on the direct measurement of image quality by computing the energy levels following wavelet decomposition using a Daubechies wavelet transform (WT). For each sub-band of the enhanced image, the energy associated is computed, and then the total average energy is estimated for all sub-bands. Visual sensitivity is then defined by comparing the total average energy levels of the enhanced image with that of the total average energy levels of the original image. This scheme can be directly applied to the image enhancement algorithms by quantizing the wavelet energy (WE) coefficients as approximate and detailed. The coefficients of the approximation and the details measure the global and detailed enhancement of the specific image enhancement algorithm.

To validate the efficiency of the proposed work, an image QA is outlined as follows:

1. Subjective image QA based on histogram plot.
2. The conventional objective assessment based on average difference (AD), correlation quality (CQ), structural content (SC), image fidelity (IF), peak signal-to-noise ratio (PSNR), contrast enhancement performance (CEP), and luminance enhancement performance (LEP).
3. The proposed objective image QA based on energy estimation in the wavelet domain from the images obtained from standard databases. The comparison is done based on existing and proposed metrics, and image QA is performed.

The proposed approach decomposes both the original (reference) and the enhanced (modified) image using DWT followed by average energy computation. The approximate and detailed wavelet energy (DWE) coefficients estimated provides global and local quality measures, respectively. The proposed objective quality measure shows a better correlation with the subjective measure and HVS. The results obtained indicates whether the image is naturally enhanced with more or less details along with the global quality.

This article is organized as follows: Section 2 gives a brief review of previous work done. The proposed image enhancement quality measure is described in Section 3. Experimental results and analysis are presented in Section 4. The conclusion is presented in Section 5.

2 Related Work

A number of metrics have been developed by many researchers for evaluating color image enhancement quality. The conventional quality measures [8] used in most of the image enhancement algorithms are listed in Table 1. $I(i, j)$ and $\hat{I}(i,j)$ denote the pixel values of the original and enhanced images, respectively. These metrics offer closeness between the two digital images by exploiting the difference in the statistical distribution of the pixel values. The two graphical measures used for assessing the quality of gray or color images are histogram and Hosaka plots. However, the graphical measures fail to produce satisfactory results for color images.

Table 1. Image Quality Measures.

Serial No.	Metrics	Formula
1	Mean square error (MSE)	$\text{MSE}=\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\hat{I}(i,j)-I(i,j)\right]^2$
2	Peak signal-to-noise ratio (PSNR)	$\text{PSNR}=10\log_{10}\left[\frac{L^2}{\text{MSE}}\right]$
3	Normalized absolute error (NAE)	$\text{NAE}=\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\hat{I}(i,j)-I(i,j)\right]}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|I(i,j)\right\|}$
4	Structural content (SC)	$\text{SC}=\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|\hat{I}(i,j)-I(i,j)\right\|^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|I(i,j)\right\|^2}$
5	Average difference (AD)	$\text{AD}=\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left\|\hat{I}(i,j)-I(i,j)\right\|}{M\times N}$
6	Contrast enhancement performance (CEP)	$\text{CEP}=\frac{\hat{\sigma}(i,j)-\sigma(i,j)}{\sigma(i,j)}$
7	Luminance enhancement performance (LEP)	$\text{LEP}=\frac{\hat{I}(i,j)-I(i,j)}{I(i,j)}$
8	Correlation quality (CQ)	$\text{CQ}=\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\hat{I}(i,j)\times I(i,j)\right]}{\sum_{i=1}^{M}\sum_{j=1}^{N}I(i,j)}$
9	Image fidelity (IF)	$\text{IF}=1-\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\hat{I}(i,j)-I(i,j)\right]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j)\right]^2}$

(**Table 1.** Continued)

Serial No.	Metrics	Formula
10	Normalized cross correlation (NCC)	$\text{NCC}=\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\hat{I}(i,j)\times I(i,j)\right]}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j)\right]^2}$
11	Maximum difference (MD)	$\text{MD}=\text{Max}\left\vert\hat{I}(i,j)-I(i,j)\right\vert$
12	Structural similarity measurement (SSIM)	$\text{SSIM}(x,y)=\frac{(2\mu_x\mu_y+C_1)+(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\delta_x^2+\delta_y^2+C_2)}$
13	Histogram	A histogram is a graphical quality measure that provides the probability distribution of pixel values in difference image.

Image QA [25] is an important process because it evaluates perceived image degradation, typically when compared with the ideal or perfect image. Image QA methods are broadly classified into two categories: subjective and objective techniques. The subjective method [19] evaluates image QA based on subjective image quality testing, making the observers evaluate image quality. The subjective image QA approach is time consuming because humans are not fast enough to evaluate visual perception. The objective QA metric [11] uses objective image quality testing based on mathematical computations. In this method, statistical indices are computed to specify the image quality. An objective image QA algorithm should be able to automatically compute image quality and have a high correlation with human visual perception. The objective QA algorithms are further classified into full-reference (FR), reduced-reference (RR), and no-reference (NR) criterion.

The FR QA algorithms [24] assume that the original image is free from distortion. The FR objective measures used for image QA are PSNR [7], structure similarity index measure (SSIM) [44], just noticeable difference (JND) [38], visual signal-to-noise ratio [30], visual information fidelity [30], etc. The simple quality measure mean squared error (MSE) has been used as an image QA for a very long time, but it has a very poor correlation with HVS. The MSE is computed by estimating the arithmetic difference between the enhanced and the original images. It can be easily found that some enhanced images with the same MSE may have different error severities, and some of them are much better than others, visually. Another commonly used objective quality measure is the PSNR. The

PSNR is obtained by computing the MSE. The PSNR, similar to MSE, does not correlate well with the perceived quality measurement. The limitations of HVS-based methods have been briefly described by Wang et al. [36]. In this scheme, the authors claim that SSIM outperforms the state-of-the-art perceptual image quality metrics. However, SSIM is a single-scale approach because scale selection depends upon the resolution and viewing distance. To overcome the drawback of the single-scale approach, a multiscale structure similarity measurement has been proposed in another work of Wang et al. [35]. However, this technique works only for the luminance component and may not be suitable for another component.

An RR QA algorithm [21] is fully generic and requires a partial knowledge of the reference image along with the distorted image. This scheme is an elaborate model of HVS. The QA in this method is based on the compution of the Kullback–Leibler divergence between the parametrized distribution of the reference and the empirical distribution of the distorted image. The RR algorithm offers satisfactory results only for specific distortion categories. The previous work on the nonstatistical RR technique computes a generalized norm between the selected wavelet coefficients of the reference and distorted images [4]. The coefficients are selected in such a way that it reduces the data required and offers a better performance compared with the other methods. Gao et al. [10] proposed an RR image QA by incorporating the merits of multiscale geometry analysis, contrast sensitivity function (CSF), and JND of Weber's law. This scheme correlates well with human perception. However, there is still a considerable room for the improvement of the RR image QA. The NR criterion [2] do not require any information about the reference image.

Algorithms based on multiscale geometric analysis such as curvelets, bandlets, wavelets, and contourlets were developed by Gao et al. [10]. This scheme depends on the constraint that needs a delicate adjustment with various databases. Moreover, the performance of this method degrades severely with the reduction in the data rate necessary for the reference. The technique proposed by Xue at al. [40] based on the Weibull statistics of the wavelet coefficients achieves a better performance at the data rate provided. However, the performance of the algorithm degrades with the reduction in data rate. The bandwidth efficiency for applications such as video conferencing and video on demand can be improved using image QA techniques. In addition, image QA algorithms [11, 25, 33, 37] are used in the optimized design of various components of an image processing system. Li et al. [20] proposed a metric that applies the directional filter bank and the CSF to wavelet decomposition. The metric is calculated based on the threshold value of the wavelet coefficients. This threshold value determines whether a wavelet coefficient is visually sensitive. The metric compares the huge number of visually sensitive coefficients between the reference and the distorted images.

The image quality measurement and human vision system are closely related disciplines. Therefore, research on image and video QA may provide deep insights into the functioning of HVS. The quantitative evaluation of image enhancement methods focuses on several criteria such as edges, sharpness, and details of an image. The color of the processed image as well as its constancy throughout the image is also a significant factor for evaluating image quality. The conventional metric [5] measures the image enhancement performance by comparing the distance between the original and the processed image. However, these techniques do not correlate well with the perceived quality, and their limitations [31, 42] have been widely recognized. Therefore, in this article, the wavelet domain has been exploited for image FR QA. The proposed method is based on energy computation in the frequency domain following the wavelet decomposition of the original and enhanced images. The suggested method is based on objective image QA and is capable of measuring the image quality, thus efficiently highlighting both the global and local details in the image.

3 Proposed Method

The wavelet domain is a powerful and efficient technique for analyzing, decomposing, denoising, and compressing signals. In particular, the DWT breaks a signal into several time frequency components that enable the extraction of features desirable for signal identification and recognition. The DWT and wavelet theory have been developing rapidly over the past few years. In the proposed method, DWT, and its energy computation, is exploited for the visual QA of an enhanced color image. The extraction of DWE coefficient from an image provides information about image details, and the extraction of approximate wavelet energy (AWE) coefficients offers the global contrast information of an image. The WE [42] overcomes the drawback of existing metrics by providing both the global and the local information of an enhanced image in a single stretch. Therefore, the WE metric serves as an efficient and objective criterion for image QA. Yih et al. [42] exploited the discrete cosine transform energy and WE to obtain feature vectors for palm print-based biometric system. Karim and Adeli [17] used WE for incident detection. The WE feature [9, 13, 32] has been used by Toreyin et al. [32] and Ham et al. [13] for real-time smoke and steam detection in image and video streams.

The proposed method uses the wavelet domain [43] to evaluate the quality of the color image enhancement. The orthogonal WT preserves energy such that the sum of the normalized square of the wavelet coefficients by level plus the normalized square of the final-level approximation coefficients equals the normalized square of the signal. In the proposed scheme, the energy of the enhanced image is analyzed using both approximate and detailed wavelet coefficients. The approximate wavelet coefficients provide information on global image enhancement, whereas the detailed wavelet coefficients provide information on image details. Finally, these enhanced image wavelet coefficients are compared with the original image wavelet coefficients, and then, the QA of an image is made. The details of the proposed method are discussed in the following section.

3.1 Wavelet Energy

The WT is a technique for analyzing the time frequency domain that is most suited for a nonstationary signal. The WT is important for capture the localized features of the signal. A continuous wavelet transform (CWT) maps a given function in the time domain into two-dimensional function of s and t. The parameter s represents the scale and corresponds to the frequency in the Fourier transform, and t indicates the translation of the wavelet function. The CWT is defined by

$$\mathrm{CWT}(x,y)=\frac{1}{\sqrt{s}}\int S(T)\varphi\left(\frac{T-t}{s}\right)dt \tag{1}$$

where $S(T)$ is the signal, φT is the basic wavelet, and $\varphi\left(\frac{T-t}{s}\right)\frac{1}{\sqrt{s}}$ is the wavelet basis function. The DWT is normally used for short-time analysis. The DWT for a signal is given by

$$\mathrm{DWT}(m,n)=\frac{1}{2^m}\sum_{i=1}^{N}S(I,i)\varphi\,[2^{-m}(i-n)] \tag{2}$$

The WE is a method for finding the WE for one-dimensional (1-D) wavelet decomposition. In 1-D wavelet decomposition, WE and vector provide the percentage of energy corresponding to the approximation and details, respectively. The WE is computed as follows:

$$\mathrm{WE}=\frac{1}{2^{-m/2}}\sum_{i=1}^{N}S(I,i)\varphi[2^{-m}(i-n)] \tag{3}$$

In the proposed method, the WE is used as an effective and efficient metric to evaluate the quality of the enhanced image. In most of the quality assessment metrics, a high-frequency information of an image should not be sensitive to lightning changes or more prominent features in order to discriminate different objects in an image. The WE is computed using a linear combination of high-frequency coefficients after a Daubechies WT. The probability density function (PDF) of a foreground object with poor contrast and the background of an image with continuous regular coefficient values has a relatively lower WE and lower skewness of WE than a background. Thus, the PDFs for such a poor contrast object is distinct when compared with the background. The WE computed for the enhanced and the original images are compared, and the following observations are made. The higher the detailed WE coefficients, the better are the details of the enhanced image. Alternatively, the details of the enhanced image are better in large detailed WE coefficients. However, the approximate WE coefficients provide information on enhancement. The higher the approximate WE coefficients, the better is the enhanced image globally.

3.2 Comparing WE with the Existing Metrics

The WE metric is compared with commonly used metrics such as PSNR, NAE, SC, AD, CEP, LEP, SSIM, color naturalness index (CNI), and color colorfulness index (CCI). The simplest and most widely used FR quality metrics are MSE and PSNR. The PSNR of gray images needs to be in the range of 25–30 dB for better visual quality. The MSE is computed by averaging the squared intensity differences of the enhanced and the original image pixels, along with the related quantity of the PSNR. MSE and PSNR are simple to calculate, have clear physical meanings, and are mathematically easy to deal with optimization process (for instance, MSE is differentiable). However, they are not well matched to visual quality perception [20]. For best image enhancement, the NAE value needs to be small. Higher SC values indicate poor enhanced image quality. The ideal value of AD is zero.

Huang et al. [15] proposed a natural color image enhancement and evaluation algorithm based on the human visual system. In this scheme, the enhanced image is evaluated using metrics such as the CCI and CNI. The hue pixels in the HSV space are divided into three classes: skin pixels (hue value, 25–70), grass pixels (hue value, 95–135), and sky pixels (hue value, 185–260). The CNI values are computed using the expression

$$\mathrm{CNI} = \frac{n_{\mathrm{skin}} * N_{\mathrm{skin}} + n_{\mathrm{grass}} * N_{\mathrm{grass}} + n_{\mathrm{sky}} * N_{\mathrm{sky}}}{n_{\mathrm{skin}} + n_{\mathrm{grass}} + n_{\mathrm{sky}}} \tag{4}$$

where n_{skin}, n_{grass}, and n_{sky} are the total number of skin, grass, and sky pixels, respectively, and N_{skin}, N_{grass}, and N_{sky} represents the local CNI values for skin, grass, and sky pixels, respectively. The CNI value varies from 0 to 1. The CCI can be expressed as

$$\mathrm{CCI}=S+\sigma, \tag{5}$$

where S is the average saturation of the image and σ is the standard deviation. A CCI value of zero indicates that the image is achromatic, and the highest CCI value indicates the most colorful image. The best range of CNI for human perception is close to unity, and CCI varies between 16 and 20.

In recent years, a great deal of effort has gone into the development of quality metric techniques that take advantage of the known characteristics of HVS. The image quality evaluated using contrast and luminance measurements provides contrast and luminance improvement with respect to the original image. However, these schemes do not provide adequate information on the image details. The SSIM method is based on the structure comparison of the original and the enhanced images. Although SSIM uses luminance, contrast, and structure information in image quality evaluation, the method fails to produce satisfactory results for poorly blurred images. The CNI and CCI metrics provide better results compared with other existing methods. However, the algorithm is not efficient from the computation point of view. In addition, image quality evaluation based on CNI and CCI works for a certain class of images and may not offer satisfactory results for medical, facial, and aerial images. As is evident from the discussions, PSNR, NAE, SC, AD, CEP, LEP, SSIM, CNI, and CCI are not appropriate or effective approaches in evaluating the performance of the enhanced color image. Therefore, the proposed WE metric is more advanced and overcomes the drawback of existing image QA methods in a more efficient manner.

4 Experimental Results and Discussions

The performance of the proposed metric is evaluated by conducting a number of experiments on images with varying environmental conditions. Images measuring 1024×768 pixels were chosen for the image enhancement experiment. Conventional image enhancement methods such as automatic gain/offset correction, intensity transformation, histogram equalization, homomorphic filtering techniques, etc. are used by many researchers. Among them, the multiscale retinex with color restoration (MSRCR) method is a popular image enhancement technique that works well under most lighting conditions. Image enhancement schemes such as histogram equalization, MSRCR [16, 23], and improved MSRCR (IMSRCR) [27] are used to validate the proposed scheme. It can be seen from the

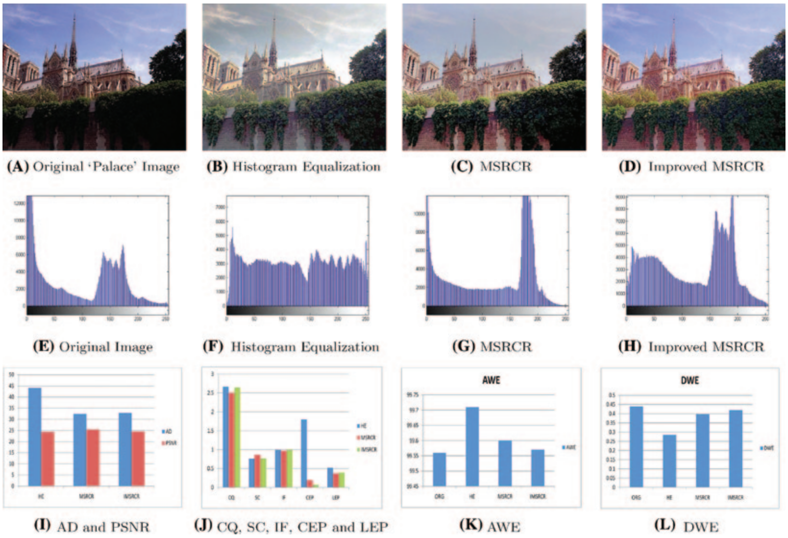

Figure 1. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Palace" Image has been Downloaded from http://visl.technion.ac.il/1999/99-07/www/.

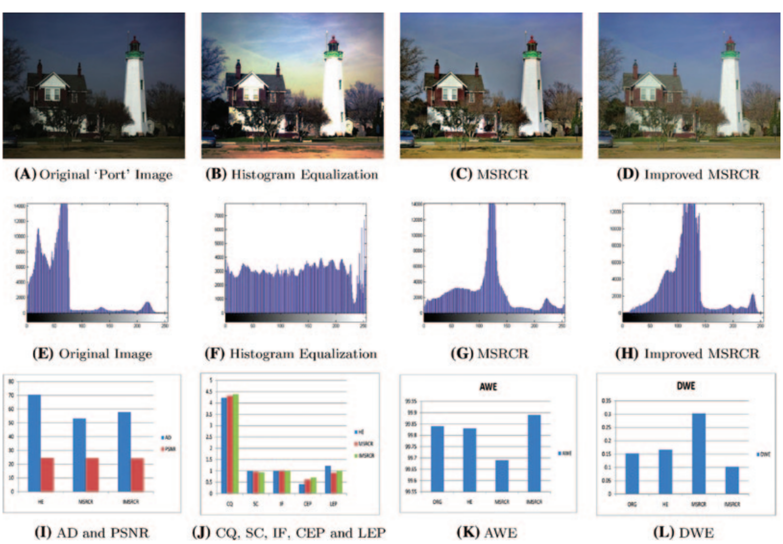

Figure 2. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Port" Image has been Downloaded from http://dragon.larc.nasa.gov/retinex/pao/news/.

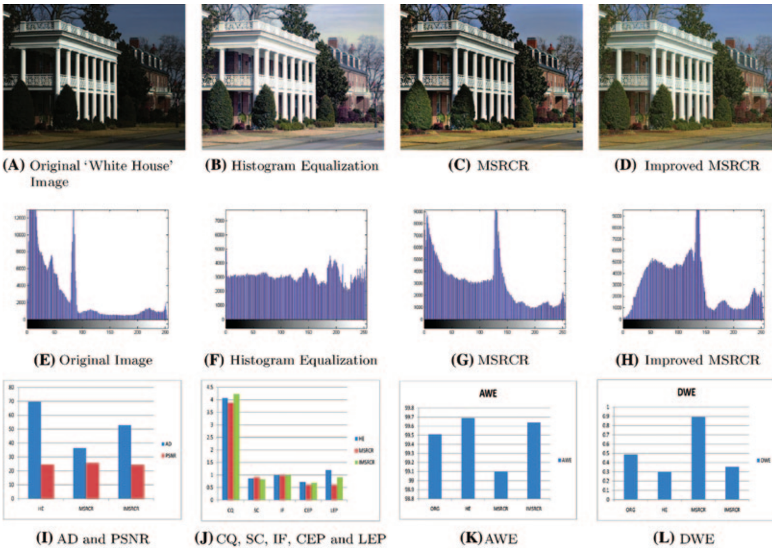

Figure 3. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "White House" Image has been Downloaded from http://dragon.larc.nasa.gov/retinex/pao/news/.

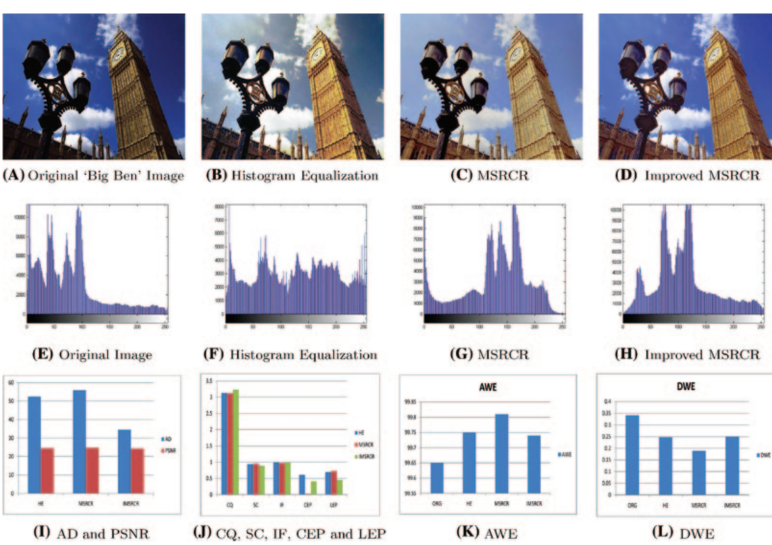

Figure 4. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Big Ben" Image has been Downloaded from http://visl.technion.ac.il/1999/99-07/www/.

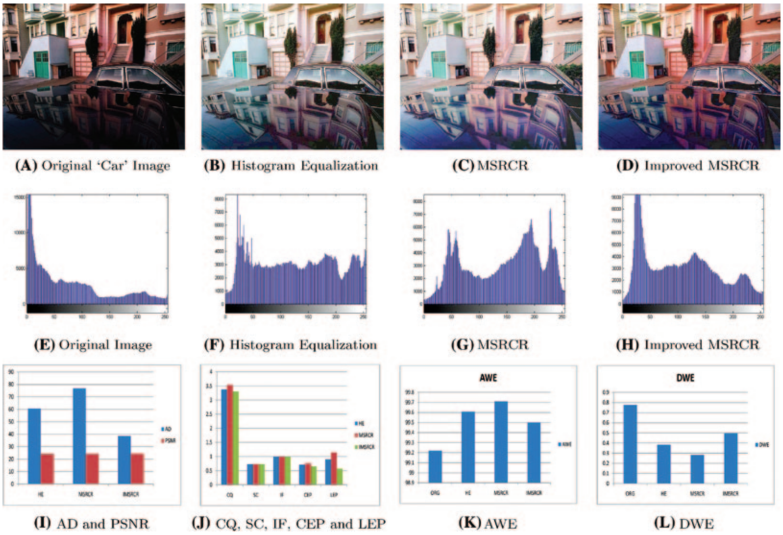

Figure 5. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Car" Image has been Downloaded from http://visl.technion.ac.il/1999/99-07/www/.

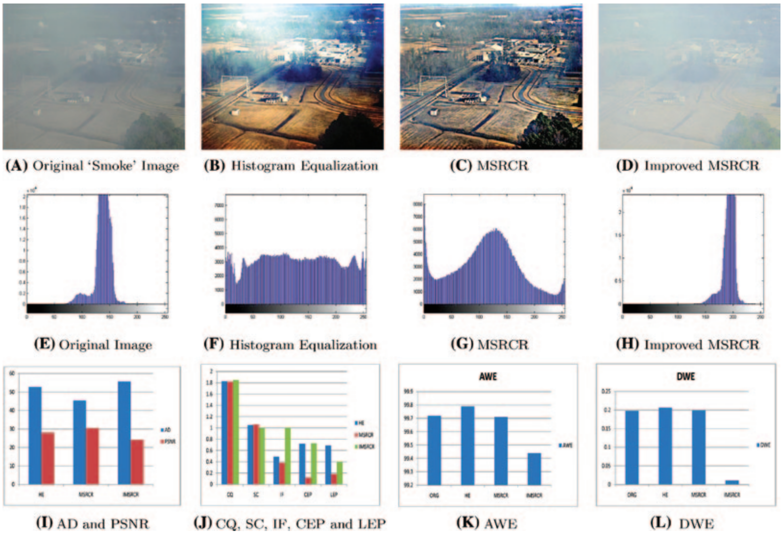

Figure 6. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Smoke" Image has been Downloaded from http://dragon.larc.nasa.gov/retinex/pao/news/.

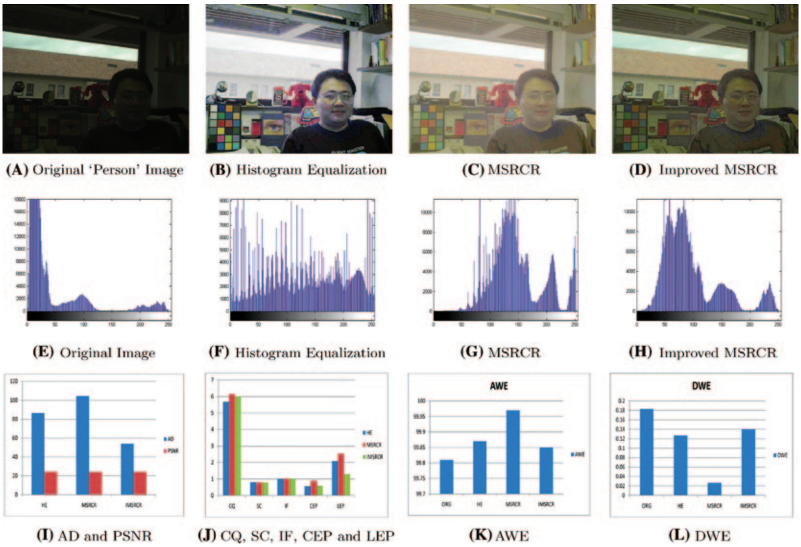

Figure 7. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The “Person” Image has been Downloaded from http://ivrg.epfl.ch/page-74617-en.html.

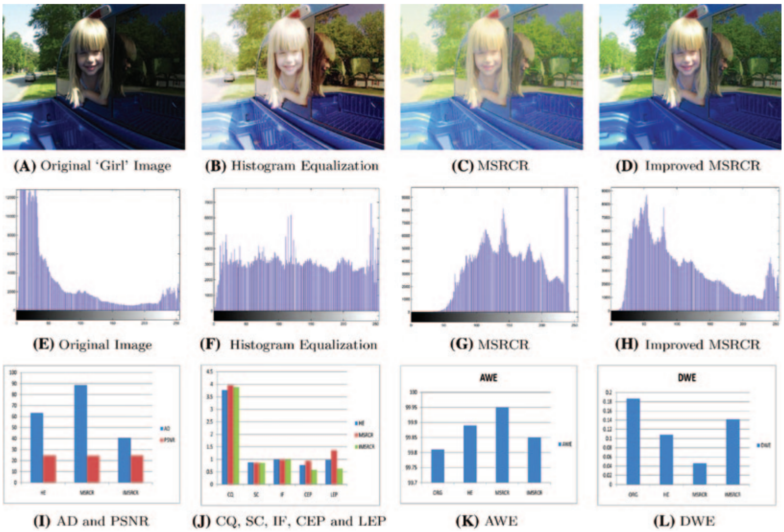

Figure 8. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The “Girl” Image has been Downloaded from http://dragon.larc.nasa.gov/retinex/pao/news/.

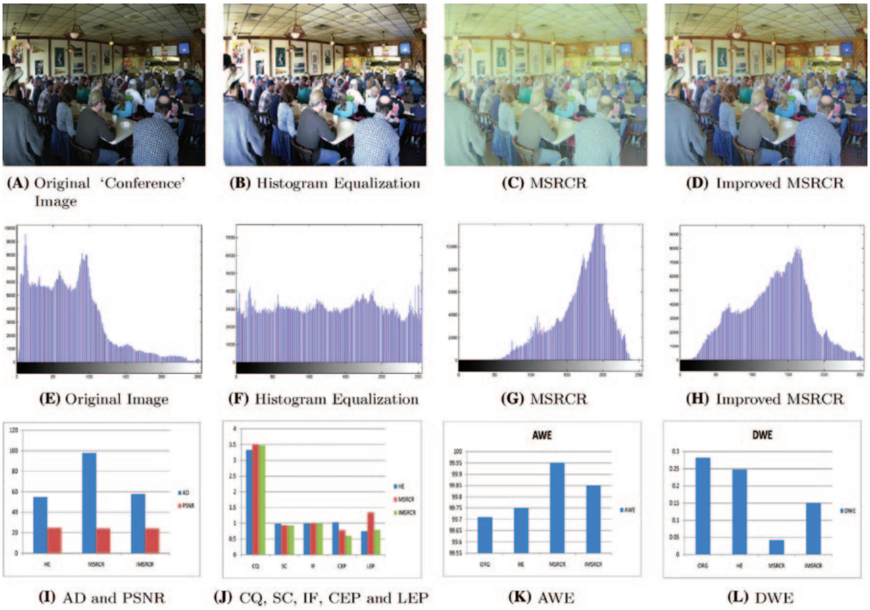

Figure 9. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Conference" Image has been Downloaded from http://dragon.larc.nasa.gov/retinex/pao/news/.

results presented that the proposed WE metric evaluates the image quality efficiently compared with the other research methods [14, 44]. The image enhancement methods adapted in this present work are coded in Matlab (version R2008a) by the authors. The reconstructed images obtained from the simulation results are presented along with the image QA.

First, a subjective image quality measure such as histogram plot has been plotted to compare various image enhancement methods. The pixel distribution swing toward the brightness region, with the appearance of peaks and valleys in the histogram owing to the natural image enhancement. Although the histogram provides a graphical measure for image quality evaluation, visual inspection reveals that the pixel distribution is independent of image details. Therefore, objective image QA metrics (AD, CQ, SC, IF, PSNR, CEP, and LEP) have been exploited to provide a comparison with the proposed metric. These metrics offers convincing results to some images but may not be used as standard evaluation methods.

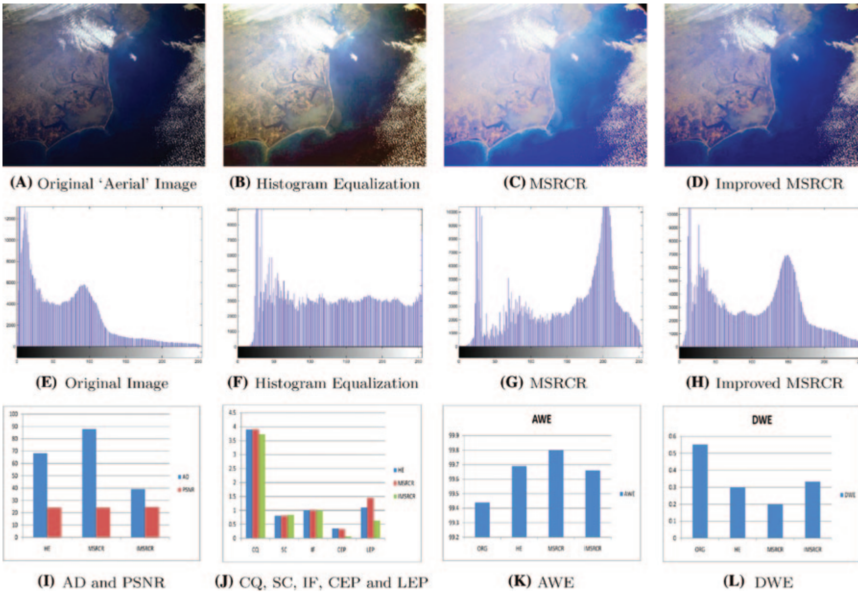

Figure 10. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Aerial" Image has been Downloaded from http://dragon.larc.nasa.gov/retinex/pao/news/.

The proposed WE-based image QA circumvents the discrepancies present in existing metrics and the human visual system. Although there is considerable progress in image QA research using objective criteria, very little work seems to have been carried out in wavelet domain-based QA. The WT is accepted to analyze signals in both time and frequency domain simultaneously and adaptively. The WT extracts the singularity structure of an image. In the present work, the original and enhanced images are transformed into the wavelet domain using Daubechies WT. It may be noted here that the WT decomposes the image into four quadrants based on frequency, namely, LL, HL, LH, and HH sub-bands. The upper left LL quadrant consists of low-pass-filtered wavelet coefficients at half the resolution of the approximated image. Subsequently, the upper right and lower left (HL/LH) blocks consist of the vertical and horizontal edges of the image at different resolutions and scales. The lower right (HH) block consists of high-pass-filtered coefficients. In this block, the edges of the image in the diagonal direction can be seen clearly. Analysis shows that the standard deviation of the wavelet coefficients varies in accordance with image quality. In agreement with this, the image

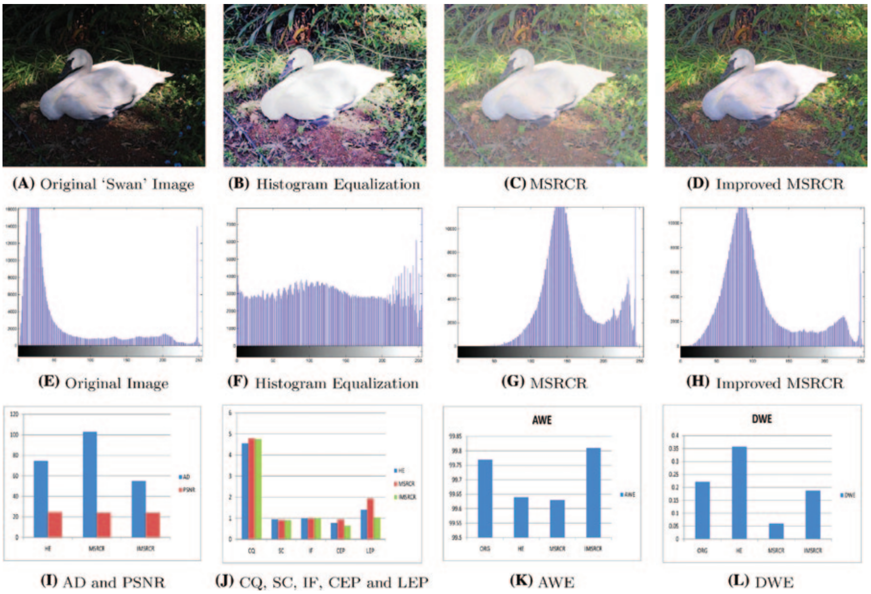

Figure 11. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Swan" Image has been Downloaded from http://www.cs.huji.ac.il/~danix/hdr/enhancement.html.

quality in the proposed method can be measured by analyzing the characteristics of the energy coefficients.

Elaborate experiments were conducted on a variety of test images. As an example, seven test images, namely, "palace," "port," "white house," "Big Ben," "car," "smoke," and "person" were presented in Figures 1–7, respectively. Image QA based on the proposed WE metric has been compared with other objective metrics to validate the proposed method. Referring to Figures 1–7, (A) shows the original image. The same image enhanced using histogram equalization is presented in B. The reconstructed image using MSRCR [16] enhancement scheme is presented in C. The image enhanced using IMSRCR method proposed by Shen and Hwang [27] is shown in Figure D. The subjective image QA using histogram plots for the reconstructed images mentioned earlier are shown in E–H. As is evident from the pixel distribution of the histogram plots, the peaks and valley points are considered in these plots to assess the image quality. The QA based on the conventional objective metrics are shown in Figure I and J as AD, PSNR, CQ, SC, IF, CEP, and LEP. The image QA based on the proposed AWE and DWE coefficients are shown in Figure K and L, respectively.

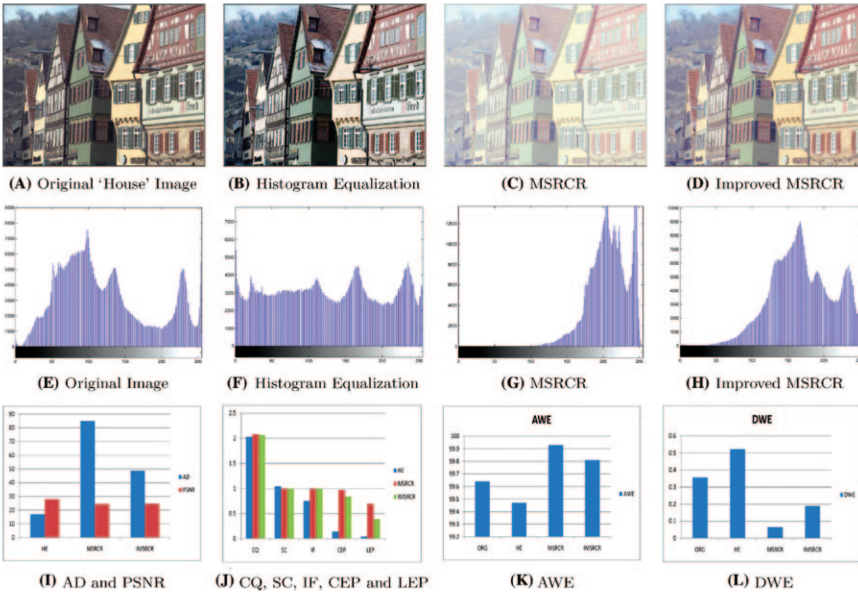

Figure 12. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "House" Image has been Downloaded from http://visl.technion.ac.il/1999/99-07/www/.

Although a good evaluation has been obtained from histogram plots, the visual inspection of the reconstructed image reveals a variance error owing to the characteristics of the human visual system. Objective metrics such as AD, PSNR, CQ, SC, IF, CEP, and LEP validates the image enhancement methods and provides a comparison with the proposed scheme. Among these metrics, PSNR is the most popular objective quality metrics for images. However, it does not correlate well with the perceived quality measurement.

The proposed WE metric for image QA offers satisfactory results compared with other existing metrics. The time frequency characteristics of WT highlights the frequency information of the image. Further, the average energy computation of each sub-band offers the strength of the global image enhancement. The analysis of both the AWE and DWE coefficients of the original and enhanced images confirms that the IMSRCR method offers a better enhancement of the "palace" image compared with other methods. The additional experimental results shown in Figures 8–13 validates the proposed method using the following test images: "girl," "conference," "aerial," "swan," "house," and "color palette."

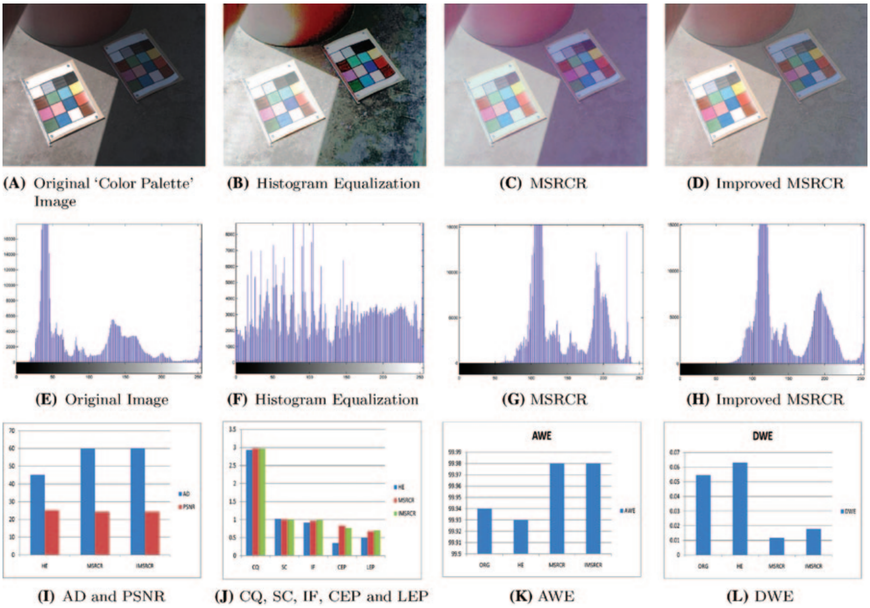

Figure 13. (Top) Image Enhancement Methods. (Middle) Histogram Plots: *x*-axis, Intensity Levels Ranging from 0 to 255; *y*-axis, Total Number of Pixels. (Bottom) Conventional Metrics and Proposed AWE and DWE Metrics. The "Color Palette" Image has been Downloaded from http://ivrg.epfl.ch/page-74617-en.html.

Table 2. Approximate (A) and Detailed (D) WE Metric for Color Image QA.

Test images	Original image		HE		MSRCR		IMSRCR	
	WE(A)	WE(D)	WE(A)	WE(D)	WE(A)	WE(D)	WE(A)	WE(D)
Palace	99.56	0.439	99.71	0.285	99.60	0.397	**99.57**	**0.420**
Port	99.84	0.152	99.83	0.166	**99.69**	**0.302**	99.89	0.103
White house	99.51	0.487	99.69	0.300	**99.10**	**0.894**	99.64	0.353
Big Ben	99.65	0.341	99.75	0.247	99.81	0.188	**99.74**	**0.250**
Car	99.22	0.777	99.61	0.384	99.71	0.282	**99.50**	**0.496**
Smoke	99.72	0.198	99.79	0.194	**99.71**	**0.199**	99.44	0.011
Person	99.81	0.183	99.87	0.127	99.97	0.026	**99.85**	**0.140**
Girl	99.81	0.187	99.89	0.108	99.95	0.046	**99.85**	**0.141**
Conference	99.71	0.281	**99.75**	**0.247**	99.95	0.042	99.85	0.149
Aerial	99.44	0.552	99.69	0.3	99.8	0.198	**99.66**	**0.333**
Swan	99.77	0.221	**99.64**	**0.358**	99.63	0.060	99.81	0.187
House	99.64	0.356	99.47	0.522	99.93	0.064	**99.81**	**0.199**
Palette	99.94	0.054	99.93	0.063	99.98	0.011	**99.98**	**0.017**

The bold values in the table show the better enhancement method based on the proposed WE metric. In the evaluation, the first preference is given for the details, followed by the overall enhancement.

Table 2 provides the AWE and DWE calculated for various test images. The values highlighted indicate that the image enhancement method offers better visual quality. This conclusion is based on the proposed metrics AWE and DWE. For instance, the DWE of the IMSRCR-enhanced “palace” image is 0.420, which is close to that of the DWE of the original image (0.439). In addition, the AWE of IMSRCR is 99.57, which is almost equal to the AWE of the original image (99.56), as explained earlier. Therefore, the IMSRCR method well outperforms while enhancing the “palace” image.

5 Conclusion

This article presents a novel FR image QA algorithm using sub-band characteristics in the wavelet domain. The existing metrics are reviewed, and the limitations are investigated. The proposed image quality evaluation is based on WE computation using a linear combination of high-frequency coefficients after a Daubechies WT. The PDF of the enhanced image has a relatively higher energy in the wavelet domain compared with other transforms. Therefore, the proposed WE has been used as an effective and efficient metric to evaluate the quality of the enhanced image. The AWE coefficients provide the information on the global image enhancement, and the DWE coefficients provide statistics on the image details. Numerous experiments on standard images demonstrate and validate the superiority and effectiveness of the proposed metric. Work is in progress on the development of a medical image enhancement algorithm based on the proposed metric.

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